

## Evaluation of a Smartphone-Based Caries Detection App in Rural Dental Camps

**Dr. Ashok HK<sup>1</sup>, Dr. Sakshi Bamba<sup>2\*</sup>, Dr. Joyson Moses<sup>3</sup>, Dr. Kunal Sah<sup>4</sup>, Dr. Nagarajan Geethapriya<sup>5</sup>, Dr. Sunira Chandra<sup>6</sup>**

<sup>1</sup>Reader, Department of Conservative Dentistry and Endodontics, Dayananda Sagar College of Dental Sciences, Bengaluru, Karnataka, India

<sup>2\*</sup>Associate Professor, Department of Paediatric & Preventive Dentistry, Government Dental College & Hospital, Srinagar, Jammu & Kashmir, India

<sup>3</sup>Professor and HOD, Department of Pediatric Dentistry, Sri Venkateshwaraa Dental College, Ariyur, Pondicherry, India

<sup>4</sup>Professor and Head, Department of Oral & Maxillofacial Pathology and Oral Microbiology, Saraswati Dental College and Hospital, Lucknow, Uttar Pradesh - 226028, India

<sup>5</sup>Professor, Department of Conservative Dentistry and Endodontics, Sree Balaji Dental college and Hospital, Chennai, Tamil Nadu, India

<sup>6</sup>Professor and Head, Department of Oral Medicine and Radiology, Saraswati Dental College and Hospital, Lucknow, Uttar Pradesh - 226028, India

\*Corresponding Author:

Dr. Sakshi Bamba

Associate Professor, Department of Paediatric & Preventive Dentistry, Government Dental College & Hospital, Srinagar, Jammu & Kashmir, India

Email ID: sakshibamba11@gmail.com

### ABSTRACT

**Aim:** To evaluate the diagnostic accuracy and feasibility of a smartphone-based caries detection application in rural dental camps, comparing its performance against clinical and radiographic standards.

**Methodology:** A prospective diagnostic-accuracy study was conducted across 12 rural camps, enrolling 582 participants ( $\geq 5$  years). Standardized intraoral images were analyzed by the app's AI model and compared with ICDAS-based examinations by calibrated dentists.

**Results:** The app's overall accuracy was 85.4%, its per-tooth sensitivity was 87.2%, its specificity was 83.1%, and it had a significant agreement ( $\kappa=0.72$ ) with clinicians. Occlusal caries performed better (90.3%) than proximal (78.9%), and the feasibility results showed few problems with connectivity and image rejection.

**Conclusion:** The smartphone app's potential for widespread caries screening in underserved rural areas was supported by its high diagnostic accuracy, quick processing, and strong agreement with clinical gold standards.

**KEYWORDS:** Smartphone dentistry; Caries detection; Rural oral health; Teledentistry; Artificial intelligence

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### 1. INTRODUCTION

One of the most common chronic illnesses in the world is dental caries, which disproportionately affects people living in underprivileged and rural areas with little access to regular dental care. Despite their effectiveness, traditional caries detection techniques like visual-tactile examination and radiography are less practical for widespread community screening because they need skilled dental personnel, specialised tools, and clinical settings. Digital technologies, especially mobile

health (mHealth) tools, have become promising adjuncts for caries detection in resource-constrained environments in an effort to close this accessibility gap [1]. Recent developments in smartphone imaging and artificial intelligence (AI) have made it possible to create mobile applications that can identify dental cavities in real time with diagnostic precision that is comparable to that of conventional techniques. For example, Dhanak et al. [1] showed that bitewing radiographs can be efficiently analysed by AI-powered smartphone applications to detect carious lesions with a high degree of accuracy. Similar to this, Lamas-Lara et al. [2] confirmed the suitability of smartphone-based photography techniques for telerdentistry applications in places with restricted access to dental care by validating their dependability in adults. These results highlight the potential of using AI algorithms in conjunction with smartphone imaging as a scalable and affordable community-level screening method. This feasibility is further supported by pilot studies. In order to provide real-time caries detection on bitewing radiographs, Pun [3] investigated integrating mobile phones with artificial neural networks. Preliminary trials showed encouraging accuracy. AI-driven methods have been proposed to transform more comprehensive dental caries management strategies beyond detection, expanding their usefulness to patient education and preventive measures [4]. Concurrently, Chen et al. [5] conducted a thorough evaluation of mobile applications intended to prevent dental cavities and emphasised the need for thorough validation prior to broad implementation. They also noticed variations in quality and usability. These findings are strengthened by meta-analytic evidence. The robustness of AI platforms in caries detection across multiple datasets was confirmed by Abbott et al. [6], who reported pooled sensitivity and specificity values exceeding 80%. Additionally, usability studies demonstrate that both patients and clinicians find AI-enabled smartphone apps to be acceptable. When Al-Jallad et al. [7] tested the child-focused caries detection app AICaries, they found that at-home screening improved and that both parents and kids had high user satisfaction ratings. All of these studies point to AI-enhanced smartphone apps as a viable, affordable, and socially acceptable method of detecting dental cavities in underserved and rural communities. However, there are still few thorough field-based assessments available, especially in expansive community settings like rural dental camps. By assessing the diagnostic precision and viability of a smartphone-based caries detection application in rural Indian camps, the current study fills this knowledge gap.

## 2. METHODOLOGY

The purpose of this study was to evaluate the diagnostic accuracy of a smartphone-based caries detection application in a prospective, observational manner over a 12-month period in 12 rural dental camps, Kaggalipura, Gulakamale, Devarachikkanahalli (DC Halli), Gowdanapalya, Bannerghatta, Vaddarapalya, Byrappanahalli, Bilwardahalli, Boothanahalli, Gollahalli, Kannayaka Agrahara, Arekere. Convenience sampling was used to enrol 582 participants (adults and children aged  $\geq 5$  years), and eligibility was limited to those who presented with at least one erupted tooth and gave their informed consent. Active oral bleeding, extensive prosthetic restorations covering tooth surfaces, or an inability to follow imaging instructions were among the exclusion criteria. Standardised intraoral photos of the occlusal, buccal, and proximal surfaces were taken by trained dental assistants using specific smartphones at predetermined distances, in controlled ambient lighting, and with the help of cotton rolls and cheek retractors. The app used an embedded artificial intelligence algorithm to create per-tooth caries/no-caries outputs with confidence scores after images were safely uploaded. After imaging, each participant received a reference standard evaluation using bitewing radiographs when necessary and ICDAS visual-tactile criteria by two calibrated dentists who were blind to the app results. Third adjudication or consensus were used to settle disagreements. The app's per-tooth sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) in comparison to the reference standard were the main results. Per-participant accuracy, inter-rater agreement (Cohen's kappa), feasibility indicators (image rejection rates, connectivity failures, time per assessment), and subgroup analyses stratified by lesion depth (enamel vs. dentin) and tooth surface (occlusal vs. proximal) were among the secondary outcomes. The results were reported in compliance with STARD guidelines for diagnostic accuracy studies after all data were stored in a secure REDCap database and subjected to ROC curve analysis, McNemar's test, and subgroup stratification. Before the study started, ethical approval was acquired from the local health authorities and the institutional review board.

## 3. RESULTS

Across the 12 rural dental camps, 582 participants (97%) were enlisted; after excluding unreadable images (4.3%), 11,240 analysable tooth surfaces were contributed. Of the participants, 55.1% were female and 44.9% were male, with an average age of  $27.8 \pm 13.4$  years (range: 6–64 years). In comparison to the reference standard, the smartphone-based caries detection app showed an overall per-tooth sensitivity of 87.2% (95% CI: 85.9–88.5) and specificity of 83.1% (95% CI: 81.4–84.7). The negative predictive value (NPV) was 89.6%, and the positive predictive value (PPV) was 79.8%. The diagnostic accuracy per participant was 85.4%. Consistent with previous findings on image-based detection challenges, subgroup analyses revealed that the app was more effective at detecting occlusal caries (sensitivity 90.3%) than proximal caries (sensitivity 78.9%). While dentin-level lesion detection was highly accurate ( $>90\%$ ), lesion-level analysis showed that enamel caries were more likely to be missed (false negatives 15.2%), supporting reports. The feasibility results showed that app analysis took less than 30 seconds per case, and the average time per participant for image capture and upload was  $2.7 \pm 0.5$  minutes. Similar to findings in other smartphone-based diagnostic studies, the image rejection rate (3.9%) was

mostly caused by blurry or poorly lit images. Failures to connect were infrequent (less than 2%).

**Table 1. Diagnostic performance of the smartphone-based caries detection app (per-tooth analysis)**

| Metric                       | Value (%) | 95% CI      |
|------------------------------|-----------|-------------|
| Sensitivity                  | 87.2      | 85.9 – 88.5 |
| Specificity                  | 83.1      | 81.4 – 84.7 |
| Positive Predictive Value    | 79.8      | 77.7 – 81.7 |
| Negative Predictive Value    | 89.6      | 88.2 – 91.0 |
| Overall Accuracy (per tooth) | 85.4      | 84.2 – 86.6 |

#### 4. DISCUSSION

With a per-tooth sensitivity of 87.2% and specificity of 83.1%, the current study showed that the smartphone-based caries detection application achieved high diagnostic accuracy, which is consistent with results from earlier teledentistry and automated diagnostic studies. These findings support the potential of mobile health technologies to enhance caries detection in rural areas with limited resources. The accuracy of teledentistry in diagnosing dental cavities is supported by systematic reviews. Kargozar and Jadidfar [8] demonstrated the dependability of mobile-based imaging tools by reporting that extra-oral photography techniques used in teledentistry produced diagnostic results equivalent to in-person evaluations. The potential of teledentistry for population-based programs was also highlighted by Sakr et al. [9], who showed that teledentistry using mobile photographs had strong reliability when compared with traditional clinical examinations in schoolchildren. It's encouraging to see how well kids accept smartphone-based dental exams. According to Aly et al. [10], paediatric patients tolerated intraoral cameras and smartphones well, which is important for the viability of community-level interventions. In a related study, Aly et al. [11] discovered that while intraoral cameras and smartphones provided similar diagnostic accuracy for early childhood caries, there were still issues with identifying early enamel lesions. Our subgroup results, which showed that enamel lesions were more often overlooked than dentin-level lesions, are in line with these findings. More and more sophisticated AI models are being incorporated into mobile applications, going beyond acceptance and viability. Using federated learning, Narayanan et al. [12] created an AI-based tool for detecting oral diseases that enhanced diagnostic robustness across decentralised datasets while protecting patient privacy. Similarly, to show the growing range of smartphone diagnostics beyond caries, Garg et al. [13] investigated smartphone RGB imaging in conjunction with AI to detect oral diseases earlier. In line with preventive measures in public health dentistry, Liang et al. [14] introduced OralCam, a smartphone-based self-examination platform that raised public awareness and gave people the ability to track their own oral health status. Technically speaking, intraoral photo algorithms powered by AI are still developing. An AI-based system for intraoral caries index detection was created by Adnan et al. [15], who reported excellent agreement with gold-standard evaluations. Our finding of significant agreement ( $\kappa = 0.72$ ) between app outputs and clinician assessments was further supported by AlShaya et al. [16], who demonstrated that teledentistry was highly accurate in diagnosing caries in children. While highlighting the need for standardisation, recent reviews affirm the potential of AI-assisted caries detection. While AI-based diagnostic models typically achieve high sensitivity, Al-Khalifa et al. [17] pointed out that their effectiveness varies based on population diversity, lesion depth, and image quality. Our results, which showed decreased performance for both proximal and enamel lesions, support these difficulties. Additionally, Mahrous et al. [18] showed that adult caries could be accurately detected by intraoral and smartphone cameras, though examiner calibration and image quality were still important factors in determining diagnostic accuracy. The versatility of AI-powered smartphone apps is further demonstrated by developments in algorithm design. Even with computational limitations, Boy et al. [19] achieved better performance by optimising detection models using MobileNetV2 with mixup and fine-tuning strategies, indicating the possibility of wider deployment in low-resource environments. Another aspect was brought to light by Price et al. [20]: the use of smartphone photos taken by parents for teledentistry. Their research showed that layperson participation could increase the reach of mobile caries detection in community screening programs by demonstrating diagnostic accuracy comparable to that of clinician-acquired images. The feasibility results of this study are in line with previous reports regarding implementation in rural dental camps. As a proof of the usefulness of integrated AI platforms in actual community settings, Kumar et al. [21] evaluated an AI-based oral screening solution (Logy.AI) and discovered that it was successful in identifying caries, calculus, and stains in primary care settings. All of these results demonstrate that AI apps for smartphones not only provide respectable diagnostic results but also facilitate scalable implementation in underprivileged regions. However, there are still significant obstacles to clinical adoption. The generalisability of AI models across populations may be constrained by variations in training datasets, inconsistent imaging conditions, and possible algorithmic bias [8,17]. Furthermore, careful consideration should be given to the ethical concerns of data privacy, informed consent, and the openness of AI decision-making. Before these systems are widely used, multi-center validation studies with a variety of patient cohorts and long-term follow-ups are necessary to verify their robustness. In conclusion, this study's results are consistent with an increasing amount of data demonstrating

the value of AI-powered smartphone apps for dental caries detection. These instruments can be useful supplements to community-based oral health screening in underserved and rural communities, as evidenced by their proven diagnostic accuracy, effectiveness, and patient acceptability. Smartphone-based diagnostic apps have the potential to revolutionise dental public health strategies by closing access gaps and facilitating early, equitable interventions—but only with further development, standardised procedures, and extensive validation.

## 5. CONCLUSION

The caries detection app for smartphones showed high diagnostic accuracy and significant agreement with clinical gold standards.

It worked better for lesions at the occlusal and dentin levels, but early enamel and proximal lesions remained challenging. Feasibility results confirmed the app's efficiency, speed, and low technical barriers in rural areas. All things considered, this tool has potential for community-based, scalable caries screening and early intervention in marginalised populations.

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